



Quantifying the impact – Can the design of the study affect the results?

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Introduction

There is a need for a consistent framework for classifying studies used for evaluation and decision support. At first glance these studies look similar, but in reality they can be very different.¹

Studies done by analysts (AN) of decisions, products, technologies, or services often point in many different directions. As such, conclusions from these studies are undermined by derivative perceived uncertainty and obscurity in the minds of decision makers (DM) and investors.

Sometimes conclusions from studies seem to depend more on the AN doing the study than on the specific object that is studied.

Explaining why different ANs can arrive at sometimes very different conclusions for the same object will potentially also lead to reduced uncertainty and obscurity for DMs and investors.

Taxonomy for classification²

Through literature studies of various scientific disciplines – including probability, statistics, economics, organization, and management – a taxonomy for the classification of different type of studies has been developed.

Tangibility Tangible (T) vs. Intangible (I)	Tangible things can be touched and seen in the corporeal world. In contrast, intangible things are ideas or concepts. Only hypothesis and indirect evidence can be offered for intangibles.
Repetitivity Single-period (S) vs. Multi-period (M)	Single-period is, for example, the CO ₂ emission of a given factory in only 2011. Multi-period information would be for more than one year – say, 2011, 2012, and 2013.
Scale Micro (i) vs. Macro (a)	This is a relative size scale. Micro is small compared with macro, but the absolute scale depends on relevance for the studied function or service. If a project is considered to be on a macro scale, then structural changes should be considered.
Time Retrospective (R) vs. Prospective (P)	Retrospective studies deal with what happened in the past, while prospective studies involve an estimation of future events.
Change Baseline (B) vs. Change (C)	The baseline is business as usual, while a change is anything different from the baseline.
Value Physical (Y) vs. Value (V)	A physical quality is an actual location and quantity of matter and energy in time and space. Value refers instead to the relative worth placed on that same physical entity by one or more DMs.

Classification matrix²

			Tangible (T)				(Tangible +) Intangible (I)			
			Single-period (S)		Multi-period (M)		Single-period (S)		Multi-period (M)	
			Micro (i)	Macro (a)	Micro (i)	Macro (a)	Micro (i)	Macro (a)	Micro (i)	Macro (a)
Retrospective (R)	Baseline (B)	Physical (Y)	TSi-RBY	TSa-RBY	TMi-RBY	TMa-RBY	ISi-RBY	ISa-RBY	IMi-RBY	IMa-RBY
		Value (V)	TSi-RBV	TSa-RBV	TMi-RBV	TMa-RBV	ISi-RBV	ISa-RBV	IMi-RBV	IMa-RBV
	Change (C)	Physical (Y)	TSi-RCY	TSa-RCY	TMi-RCY	TMa-RCY	ISi-RCY	ISa-RCY	IMi-RCY	IMa-RCY
		Value (V)	TSi-RCV	TSa-RCV	TMi-RCV	TMa-RCV	ISi-RCV	ISa-RCV	IMi-RCV	IMa-RCV
Prospective (P)	Baseline (B)	Physical (Y)	TSi-PBY	TSa-PBY	TMi-PBY	TMa-PBY	ISi-PBY	ISa-PBY	IMi-PBY	IMa-PBY
		Value (V)	TSi-PBV	TSa-PBV	TMi-PBV	TMa-PBV	ISi-PBV	ISa-PBV	IMi-PBV	IMa-PBV
	Change (C)	Physical (Y)	TSi-PCY	TSa-PCY	TMi-PCY	TMa-PCY	ISi-PCY	ISa-PCY	IMi-PCY	IMa-PCY
		Value (V)	TSi-PCV	TSa-PCV	TMi-PCV	TMa-PCV	ISi-PCV	ISa-PCV	IMi-PCV	IMa-PCV

Altogether, 64 different types of study are identified. Each type can normally be applied to the same object under investigation. Hence, 64 different results for the same object can be expected if different types of study are applied.

Expected uncertainty of a study²

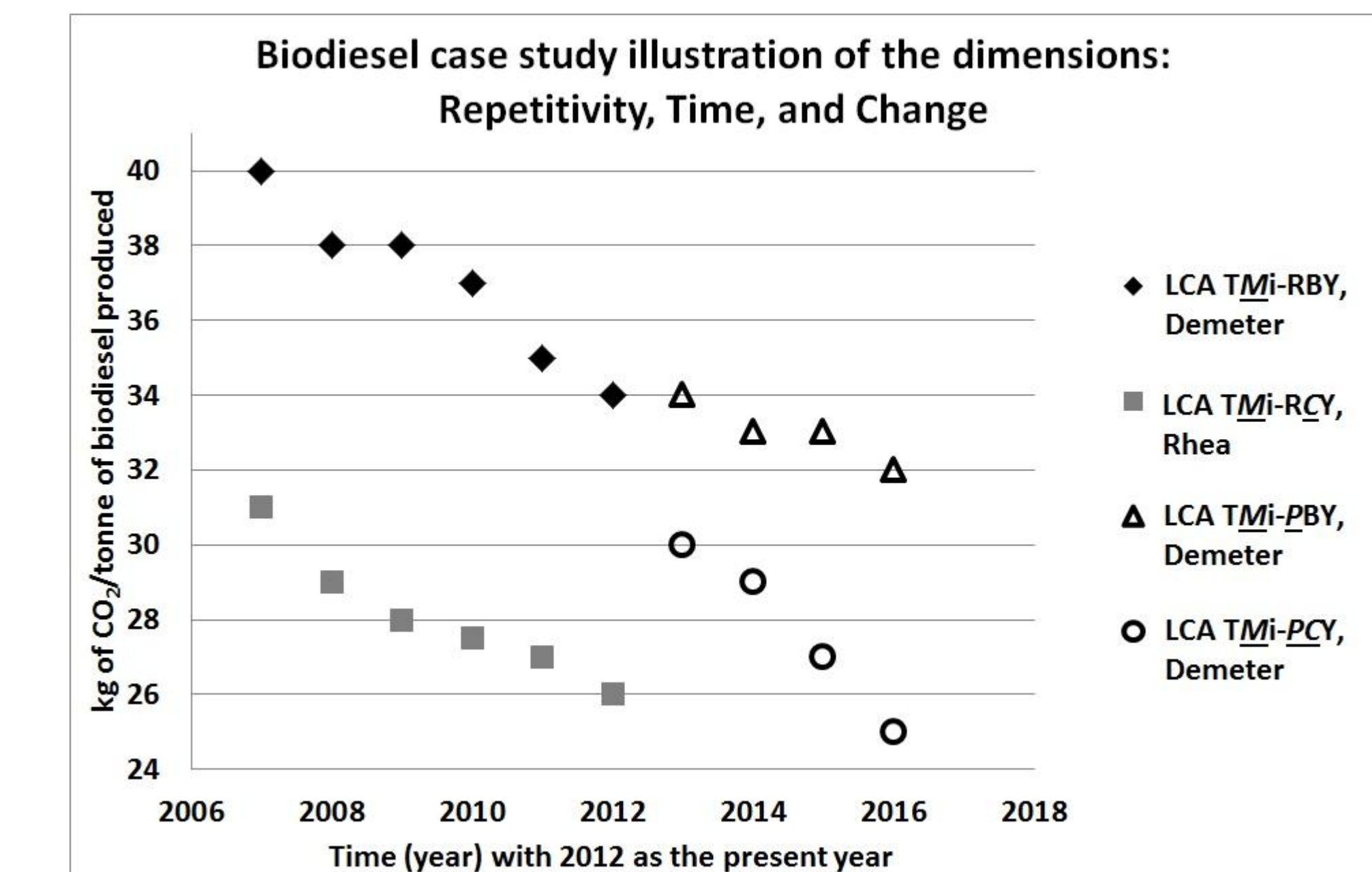
$$f(A,B,C) = E(U)$$

- $E(U)$ is the expected inherent uncertainty of a study
- A is the budget constraints for the AN
- B is the size of the study (given by the classification matrix)*
- C is the capability of the AN^{2,3}

An increase or decrease in any of the three variables A, B, or C will lead to an increase or decrease in the expected uncertainty of the given study.

*When moving in any direction from the upper-left corner cell (TSi-RBY), in general the expected inherent uncertainty of the study will increase. The more cells that are indicated with italics and an underline, the more all-embracing the study—but more uncertainty is also expected, ceteris paribus. Not including a higher level of the classification matrix means that the AN *refrains* from making statements about these more all-embracing types of study.

Biodiesel production study



What type of transesterification process should be used for producing biodiesel?

Four different types of study are illustrated here.

Should the whole time series be used, or should the naïve method⁵ be used (meaning last observed data point)?

This biodiesel study is fictive, but inspired by Herrmann et. al (2012).⁴

Conclusion and discussion

The design of a study can affect both the results themselves and the expected inherent uncertainty of the results. It is important to have a consistent framework that can clarify and classify different types of study.

The classification matrix can be used to create alignment between what the DM wants and what scientists can deliver. If the DM expects a study that reflects an *IMa-PCY* approach, but instead receives a study reflecting, for example, a *TMa-RCY* approach, then there is no alignment between what the DM wants and what the AN delivers. This leads to increased obscurity, and therefore to distorted decision support.

Importantly, this presentation does not offer any guidelines for what we *ought* to do. Rather, the classification matrix is simply a way to better describe the types of study that can be used to evaluate a decision. That is, this presentation does not suggest what a study should do with limited resources (say, just a few months with one student). Should we try to make an “all-embracing” study, as in the lower-right corner of the classification matrix, and accept the increased uncertainty? Or, would it be better to perform a more restricted study with lower uncertainty? Also, this presentation does not offer any recommendation for what level of uncertainty the DM should accept. Normally the *accepted uncertainty level* would be the decision maker’s own choice.⁶

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